2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

# Intention Recognition Using Case-base Learning in Human Vehicle

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***Abstract*** **- Most traffic accidents are caused by drivers' carelessness and lack of information on the surrounding objects. In this paper we proposed a model of human intention recognition through case-base learning and to build up an experiment system. The system can help us recognize object's intention (e.g. turn left, turn right or straight) by using detected data about human's motion, speed of the car and the distance between the car and the intersection. Furthermore, we included an example using case-base learning in this paper to improve the precision of recognition as well as an example to explain the use of the system. PC can be used to predict the driving reaction beforehand and send a warning signal to the driver in time if there is any danger.**

## I. INTRODUCTION

Vehicles are playing important roles in modern society. They make our life easier, but also cause many traffic accidents that negatively affect our life. Most traffic accidents are caused by drivers' carelessness and lack of information about the surrounding objects. The human centered Intelligent Transportation System (ITS)[1] is an expert system which links vehicles with drivers and road conditions through advanced information technology. It can improve safety and comfortableness.

To prevent traffic accident from happening suddenly, warning signal on preliminary stage is very important. Therefore, we proposed a driving support system that uses the driver's intention recognition in human vehicle system to think much like a human being. It shows only the relevant information to the driver, using the driver's intention recognition. It can avoid driver's confusion because of the information glut, and hence help him concentrate on driving.

Through the experiment, we detect drivers' motions, stepping conditions of the accelerator and the distance to the intersection, and then predict drivers' intentions through the intention recognition model, which arranges a case node. The node shows the concept. By arranging a case node, the recognition percentage can be improved with the increase in learning cases through the process of inductive learning.

## II. ARCHITECTURE OF INTENTION MODEL

As explained in the introduction, the approach of our first step is to build a system model. Here, we take some important fuzzy concepts. In this section, we introduce these basic concepts first, and then present how Intention Recognition Model works.

*A. The Recall of Abstractive Concept by Case-Base*

The concept of Fuzzy Set has been issued in past researches, and been widely known as a basic theory. The Conceptual Fuzzy Set (CFS)[2] is a fuzzy set satisfies the following conditions.

1) A fuzzy set is characterized by pairs of a label of another fuzzy set and an activation value as a grade of member.
2) Labels are structured by a knowledge representation and activation values are determined by association.

The most similar higher rank concept is recalled by activity of case.

In Fig.1, the result pet, which activates guppy and cat, is recalled. On the other hand, fish is recalled from guppy and tuna. Even though guppy and tuna exist in both cases, but we can find the concept that catching tendency is recalled respectively. This nature can be applied to intention recognition in our model.

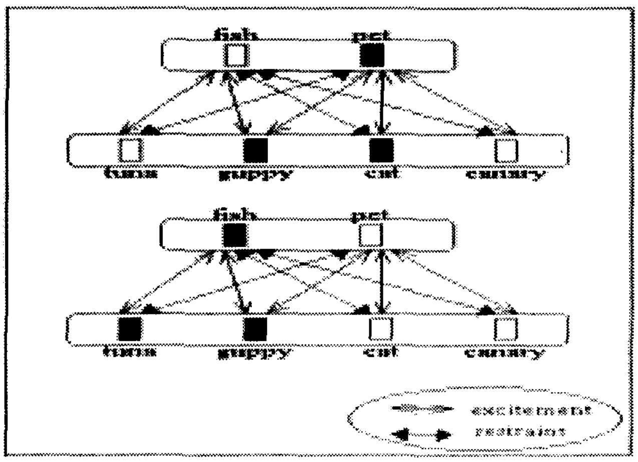


**Fig.1 Concept Recall by CFS**

*B. Fuzzy Associative Memory System*

Bi-directional Associative Memory (BAM) is the network that is composed of 2 layers as shown in Fig. 2. More than one node exists in each layer and the weight of the combination among the nodes is expressed by associative matrix of $M \in R^{n*p}$. For layer $L_A, L_B$, if this associative matrix remembers the pattern pair of $A \in R^n, B \in R^p$, even if $L_A$ layer includes noise and $A' \in R^n$ is inputted, in $L_B$ layer, B can be recalled by reverberation among layer. Oppositely, even if $L_B$ includes noise and $B' \in R^p$ is inputted, A can be recalled in $L_A$ layer.

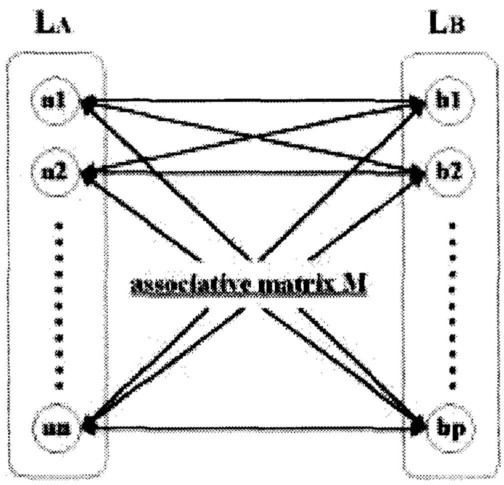


**Fig.2 Network of BAM**

The system shown in Fig.3 has *if* layer and a *then* layer. Because the correlation between the *if* layer and a *then* layer exceeds the agreement of BAM (Bi-directional Associative memory) can be memorized, one node sets the rule layer which represents one rule. Therefore, the fuzzy rule can be expressed in building BAM between *if* layer and the *then* layer.

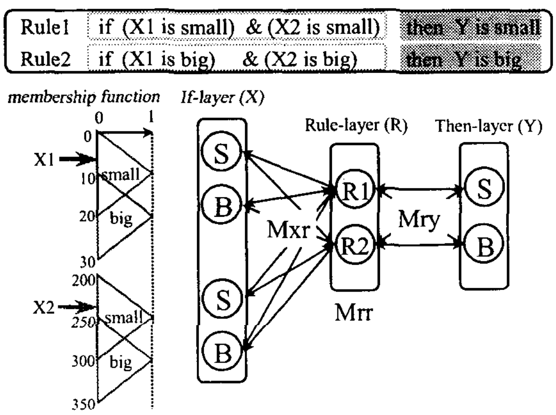


**Fig.3 Fuzzy Associative Memory**

Fig.4 shows the necessary knowledge to build associative memory.

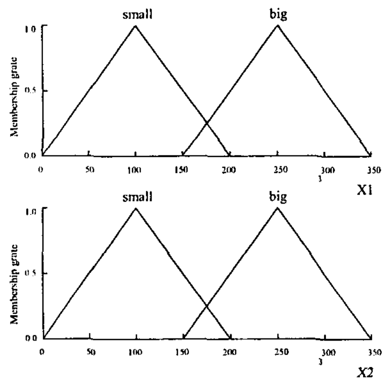


**Fig.4 Membership Function**

*C. Architecture of Intention Recognition Model*

As the technique of the knowledge architecture about intention of the human being is an ambiguous concept, we show the research, which uses knowledge expression of CFS.

In the knowledge information processing using CFS, processes of bottom-up and top down are performed complementarily and simultaneously. By the intention recognition, the knowledge about context is placed in the high rank layer, and the concrete instance is placed in the low rank layer. The concept of high rank layer is described by the concrete instance in the low rank layer. When the characteristic quantity of recognition object is obtained, nodes that correspond to each characteristic quantity of the lower rank layer are activated, and the concept node of high rank layer is activated too. At the same time, the activity of lower rank layer nodes that contradict the context in the high rank layer is restrained, and the activity of nodes that can be consented is promoted. In this way, not only the characteristic shows concrete instance, but also context is activated. Even in the case that characteristic includes noise and recognition is wrong, by the context helping recognition. The system can exclude ambiguousness and find out a right result. This recognition determined by context is called context sensitive recognition.

The intention recognition model that recognizes 3 basic intentions of turning left, going straight, and turning right is explained in Fig.5.

This model is loaded into Fuzzy Association memory system and association reasoning is executed. It is composed of 3 layers. The lowest layer is the entry layer and expresses the characteristic quantity of each operation by the membership value of the fuzzy label. The middle layer arranges the case node that shows case to be used in the process of the learning. Since it learns 3 operations for each case, totally it learns 3N patterns for N cases. In the middle layer, when the characteristic of each operation is input, the node of human being that has the most similar characteristic is activated. By the activated value distribution, we can tell the corresponding case for the operation in each part. However, only with the activated value, which appears in the middle layer, the operation intention can't be determined. This problem is solved by the introduction of context. The top layer shows operation intention and consists of three nodes corresponding to turning left, going straight and turning right respectively. The top layer is combined with all nodes of middle layer.

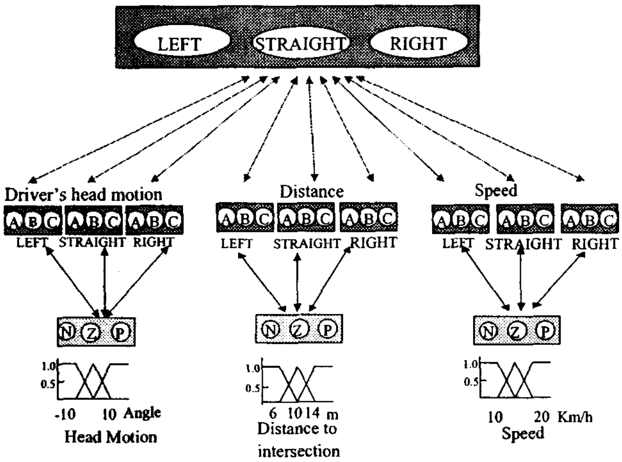


**Fig.5 Intention Recognition Model**

## III. EXPERIMENT OF INTENTION RECOGNITION

### *A. Driving Operation and Intention Recognition*

When some operations are performed, a series of operations that are decided in the degree are confirmed. The intention of operation is reasoned by detecting these series of operations. When the driver wants to turn left, he will perform such series of operations, looking straightly, checking left mirror, speeding down, then turning on the left winker, checking the left side again, and turning handle to left. Cameras and PC detect these operations and send them to the server that reasons intentions. Intention recognition is more effective for driving support in the earlier step, such as before turning on winker. It is very significant to recognize the driver's intention as early as possible then send this intention to other vehicles and pedestrians, and get necessary dangerous information from other agents.

### *B. Experiment System*

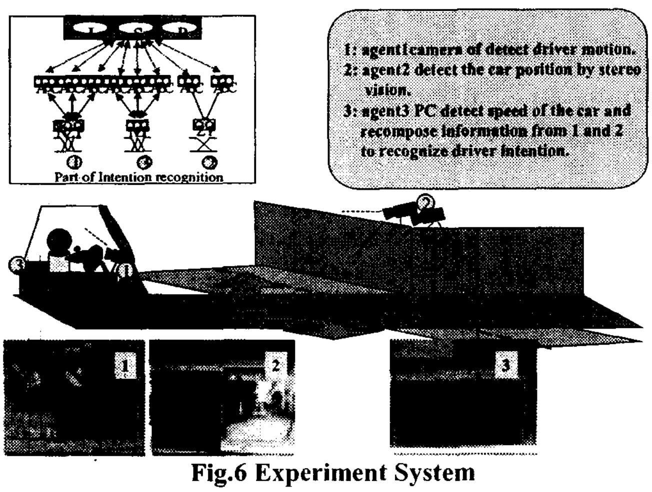


**Fig.6 Experiment System**

We use the system shown in Fig.6 to do the experiment of intention recognition. This system includes CCD cameras (agent 1, agent 2) to detect the driver's head motion and the vehicle distance to a intersection, and a control PC (agent3) to detect the speed of the car. These agents send data to the recognizing intention sever. We set cameras on the dashboard and forward of vehicle (Fig.7). We use I-Space to detect data of head motion and vehicle position. I-Space is application software; it can track motion and position of objects by color information.

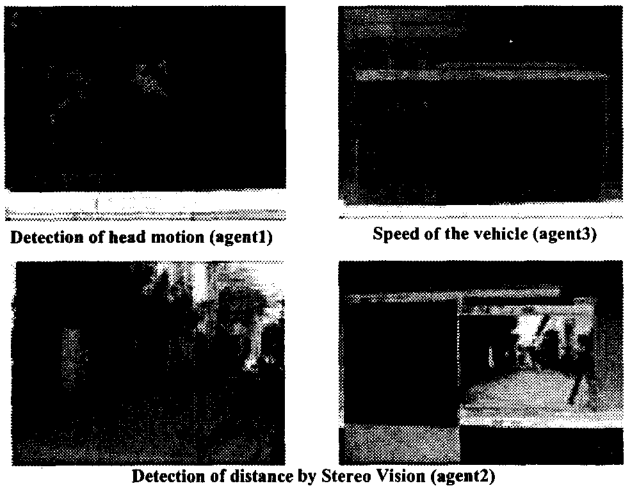


**Fig.7 Scene of Experiment**

### *C. Experiment of Case-base*

In the experiment of this research, we ask testers to drive the car (turning left, right, going straight) from the data collected: We select 7 persons' patterns of turning left, right and straight respectively. These patterns can represent all patterns that we got from the experiment. We accumulate these patterns into middle layer of intention recognition model showed in above.

In this experiment of turning left, all drivers perform such a series of operations as driving car near to intersection, looking left side mirror, speeding down, turning on the left winker, checking left side again, and then turning handle to the left. For turning to right, they perform the similar operations. It is important to recognize driver's intention at a early step, for example, before turning on a winker. So we focus on the driver's first time head motion of looking left as well as the distance and the speed at the same time. These data with characteristics are accumulated in the middle layer by fuzzy membership function to reason the intention of the driver.

Table.1 shows characteristic patterns (data detected before turning on the winker) that are used to recognize intention in this research.

In pattern A showing in Table1, the width of head is big, the distance is far, and the speed is middle. In pattern B, the width is middle, the distance is middle, and the speed is fast. The width of pattern A and pattern D are similar, but characteristic of other elements are different. So these patters have their own characteristics.

**Table.1 Driver Operation and Intention**

| Operation | | | | Intention |
|---|---|---|---|---|
| Pattern | Head motion (width) | Distance | Speed | |
| A | Large | Far | Middle | Left |
| B | Middle | Middle | Fast | Left |
| C | Small | Far | Middle | Left |
| D | Large | Near | Middle | Left |
| E | Middle | Near | Fast | Left |
| F | Small | Near | Fast | Left |
| G | Middle | Near | Slow | Left |
| | | | | |
| A | Middle | Middle | Fast | Right |
| B | Small | Far | Middle | Right |
| C | Middle | Near | Fast | Right |
| D | Small | Near | Fast | Right |
| E | Middle | Near | Middle | Right |
| F | Middle | Middle | Middle | Right |
| G | Small | Middle | Middle | Right |

Gray part is the pattern for turning left. Colorless part is the pattern for turning right. If the head motion is not detected, we consider those patterns are going straight. Note that these patterns were obtained from our experiment only. It is not applicable to general cases. . In the real world, each driver has his own driving characteristic. Thus, in order to realize their intentions, we have to get much more patterns to complete this model.

## IV. EXPERIMENTAL RESULT OF INTENTION RECOGNITION

The operation data of un-learned case is inputted into the model of intention recognition that has learned patterns of 7 peoples. The result that don't use context between top layer and meddle layer is shown in Fig.8. As a result, the node activated value distribution of middle layer is ambiguous and can't which operation intention it is. Fig.9 shows the result that used context. The fuzzy entropy decrease by the reverberation of the interactive association memory, and the node activated value distribution converges to turning left. In this way, when even the entry value and the first activated condition are ambiguous, the activated value distribution converges on the condition that depended on context.

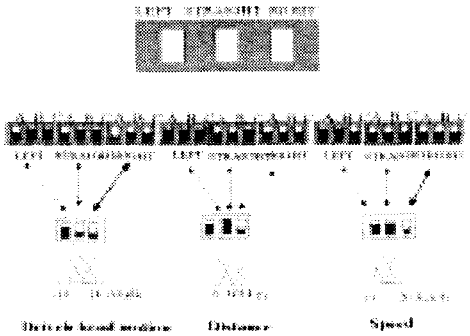

**Fig.8 Recognition Result (no Context)**

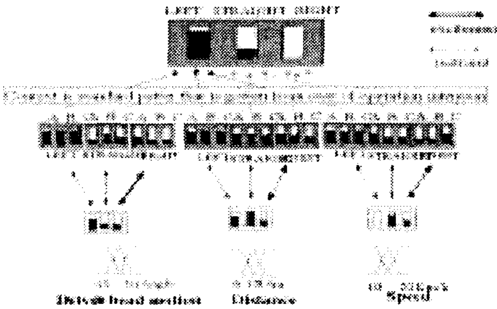

**Fig.9 Recognition Result (Using Context)**

Fig.10 shows the result of intention recognition. The data of 10 people that didn't learn, is input into model with the increment of instance, the better intention recognition ratio can be gotten. When this model learned 7instances, the ratio of turning left is 88%, straight is 95%, turning right is 86%.

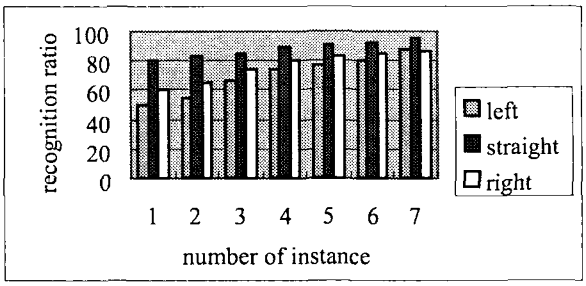


**Fig.10 Number of Instance and Recognition ratio**

## V. CONCLUSION

We proposed a model of intention recognition using case-base learning, which is based on fuzzy associative memory system. We selected characteristic operation data of turning left, turning right and going straight of 7 persons, and accumulated them into the model. After learning these training patterns, even if non-learned data is inputted, this model can recognize driver's intentions (turning right, left or straight) at an early step (e.g. before the driver turns the handle). It shows the effectiveness for driving support.

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